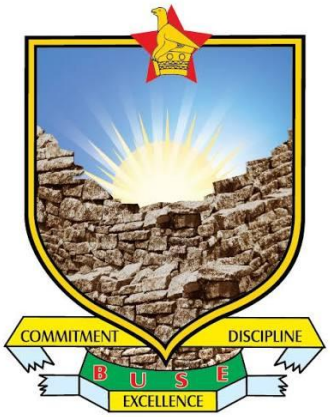
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FACULTY OF COMMERCE

DEPARTMENT OF MARKETING



SUBMITTED BY: MELINDA M MUJEGU

REGISTRATION NUMBER: B212848B

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SUPERVISOR: MR CHIRIMUBWE

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RELEASE FORM

NAME OF STUDENT : MUJEGU MELINDA

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SIGNED…. MELINDA.M. MUJEGU..... DATE...19 /06.../...2026.....

RESIDENT ADDRESS: Nyava Growth Point

Musana, Bindura

APPROVAL FORM

The undersigned certifies that the Marketing Department has supervised, read and recommended to the Bindura University of Science Education for acceptance a dissertation entitled: **THE ROLE OF AI IN REDUCING STUDENTS' DECISION-MAKING FATIGUE ON ONLINE LEARNING**

AND TEACHING EXPERIENCE AT ZIMBABWEAN UNIVERSITIES submitted in Partial fulfillment of the requirements of the Bachelor of Commerce Studies Honors Degree in Marketing.

……/…19…/…06…/…2026….

STUDENT'S SIGNATURE **DATE**

…….. ……/….19./…06…/…2026…...

SUPERVISOR'S SIGNATURE **DATE**

…..……/……/…06…/…2026…….

CHAIRPERSON'S SIGNATURE **DATE**

ABSTRACT

The study serves to find the role of ai in reducing students' decision-making fatigue on online learning and teaching experience at Zimbabwean Universities. The purpose of the study is to achieve the following objectives: to investigate the effect of AI enabled perceived usefulness and

ease of use on consumer decision fatigue (emotional distress, mental exhaustion and impulsive decision making) during online learning and teaching experience, to determine the effect of AI Trust on consumer decision fatigue during online learning and teaching experience ,to investigate if AI enabled service quality has impact on consumer decision fatigue during online learning and teaching experience and to determine if AI perceived personalized has impact on consumer decision fatigue during online learning and teaching experience. The researcher used casual research design and 383 sample size was used. To come up with a best representative the researcher used the simple random sampling procedure. The findings review that perceived usefulness and ease of use, trust in AI, AI-SERVQUAL and AI personalization have a significant effect on consumer decision fatigue (emotional distress, mental exhaustion and consumer decision fatigue).

Key words: Trust in AI, AI-SERVQUAL, Perceived Usefulness and Ease of Use, AI Perceived Personalization and Consumer decision fatigue.

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DEDICATION

I would like to thank the Almighty for his loveliness throughout. l dedicated this project to my father and my mother for always being in support of my full academic life.

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CHAPTER I

INTRODUCTION

1.0 Introduction

This section explores the background of the study giving out the problem statement, objectives of the study and hypothesis. In addition to that, it sets out the assumptions, limitations and the delimitation of the study. It also gives brief definitions to specific terms, significance of the study to business entities, the government, the researcher and students and at the end the section draws a summary of the whole chapter.

1.1 Background of the study

Artificial intelligence (AI) is the capacity of a system to precisely comprehend outside information, learn from it, and use that knowledge to achieve certain performance goals through adaptable modification (Kaplan 2019), Wang and Li (2024) found out that artificial intelligence (AI) technology becomes increasingly integrated into education, understanding the theoretical mechanisms that drive university students to adopt new learning behaviors through these tools is essential. Furthermore, they found that positive emotions, digital efficacy and satisfaction significantly affect continued AI usage. They also recommended that higher education institutions should promote AI technology to enhance student's learning. In addition, Herman and Puntoni (2024) examined AI and human behavior focusing on AI applications such as ChatGPT, Pall-E and Bard. Moen and Pasquine (2021) observed that the use of AI for decision making and autonomy is not conclusive. Rahman et al (2025) found out that capability of AI chatbots significantly influences the adoption of AI chatbots for learning effectiveness. From the above agreement there are still grey areas on the impact of AI on students online learning experience. Echterhoff, Melkote, Kancherla and Mctuley (2024) show that they can reduce the number of decisions to selection with a reinforcement learning-based Decision Minimizer Network (DMN).

By implementing a step aware reward function, they can penalize long sequences, leading to fewer decisions having to be made by humans.AI has been a topic of growing interest and investigation in various fields including higher education (Slimi 2023). Slimi study results reveal that higher education institution needs to integrate AI more extensively in their programs to prepare students for the future workforce. Vasconcelos et al (2023) observed that AI systems can improve decision making. Echterhoff et al (2024) study results show that AI can help reduce decision fatigue. Ma, Zhang and Hui (2024) results show that students AI trust moderated the mediating role of positive emotion. Persson et al (2019) observed that the doctors decision making is constant with the decision fatigue. Tyler et al (2020) observed that decision making fatigue can lead to bias, error and preventable harm. Ahuja (2019) observed the impact of AI on physicians' decision-making fatigue. Sourdin (2018) observed that AI can assist in judicial decision making. Based on the above studies there are some still grey areas to investigate on impact of ai on reducing decision making fatigue on learning and teaching experience.

1.2 Statement of the problem

The problem AI presents challenges in online learning especially when the teachers are very far away. The tertiary education industry is experiencing a rapid shift towards digitalization, yet it continues to face significant challenges related to learning and teaching decisions and students' satisfaction. These challenges are particularly evident in online teaching/learning experiences where students often struggle with issues such as decision fatigue, inaccurate answers and dissatisfaction due to poorly fitting or misrepresented errors and items (Adelakun & Adewale, 2023; Nwankwo et al., 2022). In education AI perceived usefulness and ease of use, Trust in AI, SERVQUAL and perceived personalization are very crucial.

1.3 Main objective

This study seeks to investigate the role of ai in reducing students' decision-making fatigue on online learning and teaching experience at Zimbabwean universities

1.4 Research Objectives

The study strives to attain the succeeding objectives

To determine the effect of AI Trust on consumer decision fatigue (emotional distress, mental exhaustion and impulsive decision making) during online learning and teaching experience To investigate if AI enabled service quality has impact on consumer decision fatigue during online learning and teaching experience.

To determine if AI perceived personalized has impact on consumer decision fatigue during online learning and teaching experience.

1.5 Hypothesis

H1: AI enabled perceived usefulness and ease of use has a statistically effect on consumer decision fatigue (emotional distress, mental exhaustion and impulsive decision making).

H2: Trust in AI has a statistically effect on consumer decision fatigue.

H3: AI-SERVQUAL has a statistically effect on consumer decision fatigue.

H4: AI perceived personalization has a statistically effect on consumer decision fatigue.

1.6 Assumptions

On undertaking this research, the researcher made the following assumptions: Firstly, it was assumed that the respondents were willing to actively participate in the research and provide valid, true, and unbiased information. Secondly, it was assumed that the sample used in the study was adequately representative of the entire population, ensuring that the findings could be generalized to a broader context.

1.7 Significance of the study

The study will contribute in the form of two dimensions that is to both theoretical and practical aspects;

1.7.1 To Business entities.

Universities must use study results to implement AI strategies in teaching and learning experiences.

1.7.2 To the government

The government of Zimbabwe will use the study results in setting up policies guiding use of AI at tertiary colleges.

1.7.3 To the researcher

The researcher acquired valuable experience and research skills, providing a foundation for future endeavors.

1.7.4To students

The information gathered will be highly beneficial for future researchers, particularly those who are intrigued by the topic.

1.8 Delimitations of the study

The research looked at the role of AI in reducing student decision fatigue on online learning. The study was conducted in Bindura area despite the fact that the universities are located in different parts of the country. It was important to the researcher to carry out the research close to home since it covers the gap in the financial crisis of travelling from one city to another. The time period of research was limited to 8 months (from October 2024 to June 2025).

1.9 Definition of key terms.

Artificial - intelligence is the process of using AI capabilities like data collection, data-driven analysis, natural language processing and machine learning to deliver customer insights and automate critical marketing decisions

Consumer decision -is a series of steps an individual under goes to make a purchase

Perceived usefulness and ease of use- refers to the degree to which a person believes that using a particular technology will enhance their job performance or overall effectiveness

Trust in AI- refers to the confidence that users, stakeholders and society have in artificial intelligence systems and their outcomes.

AI-SERVQUAL- is an adaption of the SERVQUAL model which is traditionally used to measure service quality in various industries.

AI Perceived personalisation- refers to the degree to which users feel that artificial intelligence systems tailor experiences, recommendations and interactions to their individual preferences behaviours and needs.

Consumer decision fatigue- a state of mental overload that impedes a customer's ability to continue making decisions. In this study the focus is on emotional distress, mental exhaustion and impulsive decision making.

Emotional distress- is any uncomfortable or unwanted emotions that come up when you experience challenges or difficulties

Mental exhaustion -refers to feeling mentally depleted, often accompanied by apathy, pessimism, irritability, and emotional reactivity

Impulsive decision making -is when you act quickly with no thought to the consequences. There's nothing on your mind beyond that exact moment

1.10 Limitations of the study

The sample size comprised of tertiary students only which can be difficulty to generalize. The study was carried out in a short time instead of a long time of 2-3 years

1.11 Chapter Summary

The chapter started by looking at the background of the study, the problem questions which makes the whole study worth statement of the problem and delimitations of the study, its limitations and assumptions. The chapter is closed by the definition of terms.

CHAPTER II

LITERATURE REVIEW

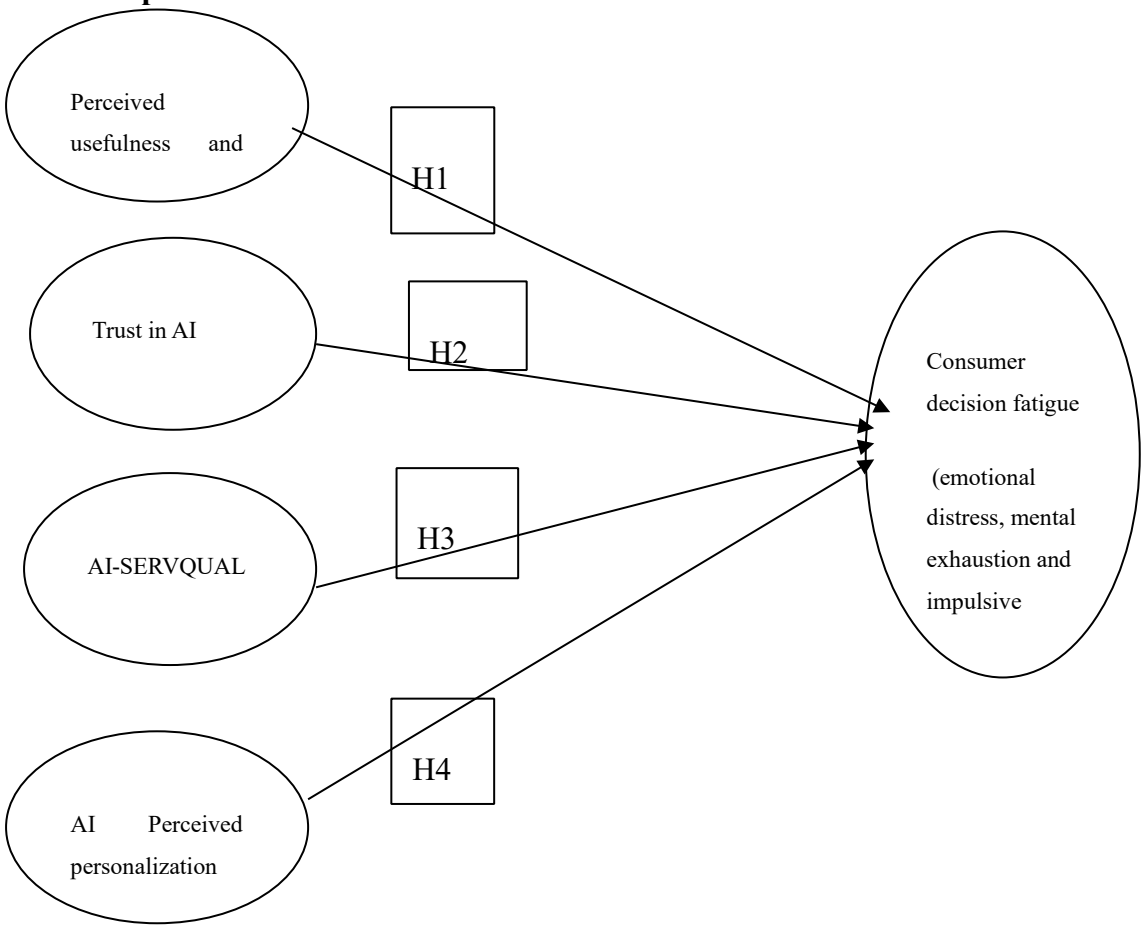
2.0 Introduction

This chapter focuses on exploring the current literature relevant to the topic. It features an examination of conceptual and theoretical frameworks, empirical evidence and gap analysis. It concludes with a summary of the reviewed literature.

2.1 Conceptual framework

Conceptual framework defines the relevant variables for the researcher's study and maps out how they might relate to each other. Fig 2.1 presents a conceptual framework.

Figure 1 Conceptual Framework



2.2.1Artificial Intelligence

Artificial intelligence (AI) simulates human cognitive processes, enabling tasks such as learning, reasoning, and problem-solving (source). It encompasses technologies like machine learning and natural language processing, which enhance data analysis and user interaction (source). Russell et al. (2020), defines Artificial Intelligence as the capability of a machine to imitate intelligent human behaviour. The roots of AI research date back to the 1950s, with significant contributions from pioneers like Turing and McCarthy (2019), who aimed to create machines that exhibit intelligent behaviour.AI significantly improves operations and services globally. Wichert (2020) highlights its application in quantum computing and machine learning, which allows for rapid

problemsolving in complex scenarios that exceed human processing capabilities. The advancements in AI continue to evolve, promising ongoing benefits even as technology develops. AI plays a crucial role in enhancing the online teaching /learning experience by personalizing interactions and mitigating decision fatigue. Tools such as chatbots and recommendation algorithms analyse consumer behaviour, enabling retailers to implement tailored marketing strategies. By leveraging AI to streamline options and enhance personalization, retailers can effectively combat decision fatigue, improving students' satisfaction and engagement. Netragaonkar (2024), states that the aim of AI is to improve computer functions, which are related to human knowledge for example reasoning, learning and problem solving.AI gives opportunities to higher education services to become easily accessible at an extraordinary speed, not only inside the class but also outside the classroom. AI has the potential to automate and democratize personalized adaptive learning for students. It will help to mitigate the learning gaps, generate learning interests among students, increase-learning ability, and language affinity and improve learning pace (Wing and Li 2024).

2.2.2 Perceived Usefulness and Ease of Use

Perceived usefulness and ease of use refer to the degree to which a person believes that using a particular technology will enhance their job performance or overall effectiveness. (Davis et al (1989). Perceived usefulness of ease and use is the degree to which a person believes that using a particular system would be free from effort Davis (1989). Perceived usefulness of ease and use is the degree to which individuals perceive how easy it is to use the technology Davis et al (1989). This study sheds light on the anticipated changes in consumer behaviours resulting from the adoption of generative AI technology. It explores how generative AI tools will shape consumer decision-making processes, preferences, and overall brand interaction.

2.2.3 Trust on AI

Trust in AI refers to the confidence that users, stakeholders and society have in artificial intelligence systems and their outcomes (Afroog, Akbari and Malone,2024). Trust in AI systems refers to users' confidence in the reliability, fairness, transparency and accuracy of an AI's decision (Afroog, Akbari and Malone,2024). Trust in AI is the willingness of people to accept AI and believe in the suggestions, decision made by the system, share tasks, contribute information and provide Afroog, Akbari and Malone (2024). Trust is of great importance in online commerce. According

to Kim, Ferrin and Rao (2008), consumer confidence has a positive effect on a consumer's intention to buy. The higher the consumer trust in an online shop is, the more likely the consumer will be to go re through the buying process. Trust is especially crucial when the customer perceives a financial risk. Thatcher et al. (2013) identified two types of trust: general and specific trust. General trust concerns the e-commerce environment, consumer beliefs about and attitudes towards it. Specific trust is related to the shopping experience in a specific virtual store. Confidence can be enhanced through interactive communication between AI and the buyer by using appropriate product descriptions and images to reduce the perceived risk. Cătoiu et al. (2014) state that there is a strong negative correlation between perceived risks and trust. According to Reichheld and Schefter (2000, p. 107), "price does not rule the Web; trust does "Additionally, businesses and developers of generative AI tools are responsible for prioritizing transparency, accuracy, and accountability to build trust with consumers. Credibility and trust can be enhanced by ensuring clear disclosure of AI-generated content and incorporating mechanisms for user feedback and verification.

2.2.4 AI-SERVQUAL

AI-SERVQUAL is an adaption of the SERVQUAL model which is traditionally used to measure service quality in various industries (Parasuraman et al., 2005) .AI-SERVQUAL can be defined as a framework that evaluates the quality of AI services based on user expectations and perceptions. (Parasuraman et al., 2005). In conclusion, learning and applying AI-SERVQUAL is essential for learners, as students are provided with knowledge and understanding to their expectations and perceptions of the usage of AI-based services. Identifying the gap between expectations of student and the perceived service quality, business may have necessary and actionable improvements to design their AIs.

2.2.5 AI Perceived personalisation

Perceived AI personalization measures to what extent users perceive that artificial intelligence services personalize its responses and experiences with reference to their own preferences and their behaviours (Smith and Chaffey, 2019). Smith and Chaffey (2019, AI perceived personalization the utilisation of artificial intelligence to tailor messaging, recommended goods or services and the delivery of other services to individual users. 2019 Haynes and Downie Perceived personalization-extent to which a consumer perceives a product or service customised to individual preferences.

Smith & Chaffey (2019), It can also be described as the perception that a brand understands and caters to the unique needs and desires of its customers Johnson (2020). According to Smith & Chaffey (2019), perceived personalization is essential for improving students learning experience and satisfaction in digital environments. Johnson (2020) further emphasizes that data analytics is crucial in crafting personalized learning and teaching experiences that resonate with students. Lee et al. (2021) support this notion, stating that a strong sense of personalization can significantly alleviate decision fatigue among students.

2.2.6 Consumer decision fatigue

Consumer decision fatigue refers to the deteriorating quality of decisions made by an individual after a long session of decision making. Tierney, J. (2011) defined consumer decision fatigue as the tendency for people's decision making to become impaired as a result of having recently taken multiple decisions. Consumer decision fatigue is a result of unconscious, psychobiological processes and is a reaction to sustained cognitive, emotional and decisional load, as opposed to a trait or deficiency Tierney, J. (2011). Consumer decision fatigue involves many elements but, in this study, focus on only three which are emotional distress, mental exhaustion and impulsive decision making. Emotion distress is any uncomfortable or unwanted emotions that come up when you experience challenges or difficulties Tierney, J. (2011). Emotional distress, particularly in the context of online shopping, can manifest as consumer decision fatigue, characterized by feelings of overwhelm, anxiety, and frustration when faced with numerous choices. American Psychological Association (2022) states: This a state where a people experience Emotional suffering related to stressor and demand that is challenging to handle this term applies perfectly for consumer because on this digital marketplace. National Institute of Mental Health explains (2013) : It covers a range of emotions such as sadness, anxiousness and frustration, stemming from various aspects of our life The huge amount of options for students on the digital marketplace are one of those factors The World Health Organization (2022) adds that, this condition of a person: affects people in their emotional and psychological and the social aspect which shows, the decision making part of the online shoppers can cause problem and students decision fatigue has to be avoided. The result from extensive effort of thinking: (Leiter, M. P., & Maslach, C. 2016) also termed as fatigue resulting from excessive intellectual functioning: an unable to concentrate: in an overwhelming or exhaustive capacity due to mental process; an unable to focus clearly. The term mental fatigue is referred as in (Leiter, M. P., & Maslach, C. 2016): It denotes mental processes

and reduced capacity in thinking by means of continuously or intensive cognitive workload. The inability to focus on tasks or make sound decision as the results of a long period of Stress or information overload; these problems will definitely present when it comes to online shoppers dealing with numerous of product selection and huge information provided in those selected options (Taylor & Smith, 2018). Roberts (2020) emphasizes that an abundance of choices necessitates streamlined learning experiences to mitigate mental fatigue. If left unaddressed, mental exhaustion can lead to decreased students' engagement and satisfaction, as highlighted by Nguyen et al. (2021). Understanding and addressing mental exhaustion is crucial for students, as it directly affects students learning ability and decision-making.

Impulsive decision-making is when you act quickly with no thought to the consequences (Rook, D. W., & Fisher, J. 1995). Impulsive decision-making can be referred to as spontaneous purchasing behaviour without thorough consideration. (Rook, D. W., & Fisher, J. (1995). Impulsive decisionmaking can be defined as the tendency to make decisions based on immediate desires, often resulting in a lack of foresight regarding the consequences of those purchases. (Khan & Rahman, 2019). It is characterized by quick, unplanned actions driven by emotional triggers rather than rational thought. Additionally, this behaviour can lead to students' remorse towards sustainable learning (Khan & Rahman, 2019). Impulsive decision-making is often influenced by emotional triggers and it can be exacerbated by the ease of online learning and teaching experiences Understanding impulsive decision-making is crucial for students as it can significantly impact satisfaction

2.3 THEORETICAL FRAMEWORK

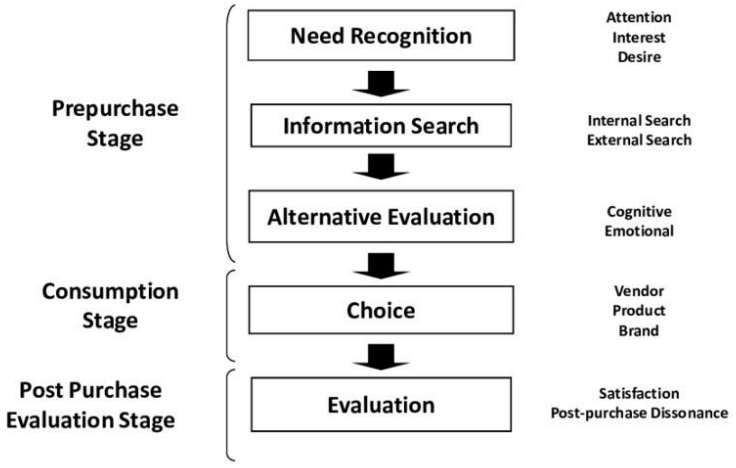
Learning at universities can result in the proliferation of a lot of information can lead to consumer decision fatigue, a phenomenon that significantly impacts students learning experience. As students increasingly leverage artificial intelligence (AI) to enhance the learning experience, it becomes essential to explore the theoretical frameworks that underpin students' interactions with technology. Three main theories will inform this theory framework, which are: the Service Quality Model (Parasuraman et al., 1988), the Technology Acceptance Model (TAM) (Davis, 1986), and the Decision-Making Process Theory (Simon, 1955). These 3 theories help explain AI's ability to

reducing decision fatigue through service quality, technology acceptance and simplifying decision making process. By combining these theories, we will be better equipped to examine how AI affects online consumer experiences.

2.3.1 Decision Making Process Theory (Simon, 1955)

This decision making theory suggests a step-by-step process through which choices can be effectively made, including the identification of the problem, search for information, appraisal and evaluation of alternatives and, the choice of one alternative over others (Simon, 1955). In an online teaching / learning experience environment the student may find their decisions to be an overwhelming process as there are so many options to choose from, which would contribute to the student's 'decision fatigue.' AI would therefore assist students by making the appropriate information readily available, reduce the burden of choice on the students while evaluating the decision and offer them choices they would preferred. This also ensures that the online teaching / learning experience choice taken by the student meets their needs as also supported by Simon's decision making process. The decision making theory is summarized and highlighted in the figure below.

Figure 2 Decision Making Process Theory (Simon, 1955)

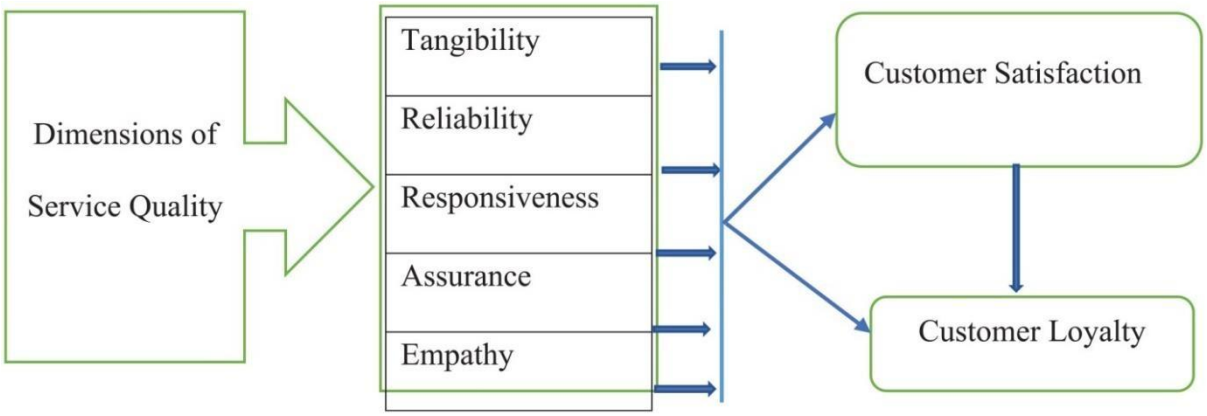


2.3.2 Service Quality Model (Parasuraman et al., 1988)

Service Quality Model. This Model stressed that Service Quality was one predictor on the student's satisfaction and loyalty of which it consist of 5 dimensions: 'tangibles, reliability, responsiveness, assurance, empathy. In online learning context, Al can be used to enhance each of the dimensions through personalized recommendation, provides valid information to the student as well as speedy assist to the student. For example, a specific Al can predict individual learning's tendency by understanding students learning behaviour, and generate a personalized knowledge display in order to lessen their decision-Making load. With improvement of Service Quality thru Al, it enable the students to achieve more desirable teaching/learning experience and at the same time it relieve consumers of this decision fatigue. The Service Quality Model has been illustrated in Fig 2.3 as follow: 22

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Figure 3 Service Quality Model (Parasuraman et al., 1988)

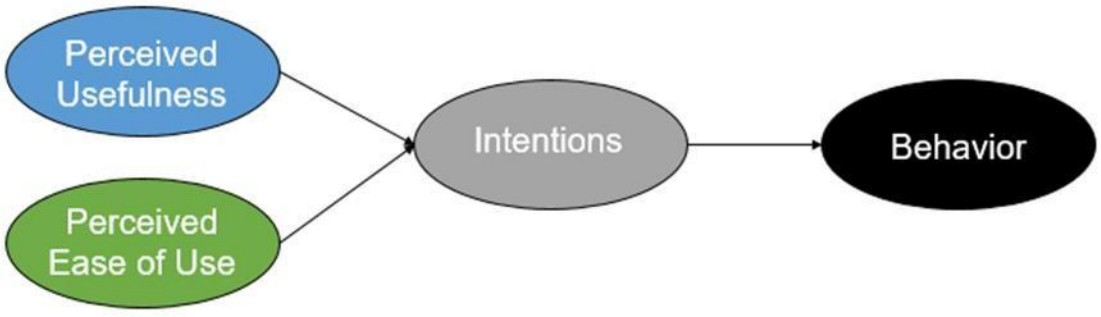


Source Parasuraman et al., (1988)

2.3.3 Technology Acceptance Model (TAM) (Davis, 1986)

TAM claims that the key variables influencing technology acceptance are the perceived ease of use and the perceived usefulness. In the context of online learning, AI technologies must be perceived as beneficial and user-friendly for students to embrace them fully. When AI tools, such as chatbots and personalized recommendation systems, are designed to enhance the learning experience without adding complexity, students are more likely to accept and utilize these technologies. By fostering a positive perception of AI's usefulness and ease of use, students can engage with AI-driven solutions, thereby reducing the overwhelming nature of choice and alleviating decision fatigue. Figure 2.4 below summarizes the TAM model.

Figure 4Technology Acceptance Model (TAM) (Davis, 1986)



Source Stoel et al (2008)

2.4 Empirical Evidence 2.4.1 AI Perceived Usefulness and Ease of Use and Consumer Decision Fatigue (Emotional

Distress, Mental Exhaustion, and Impulsive Decision)

Abidin (2024) conducted the effect of perceived usefulness, perceive of use and lifestyle on purchase intention. The finding show that the perceived usefulness of this study has proven to be positive but insignificant to consumer purchase intention. Lopes et al (2024) investigated psychosocial factors in ease of use and their effect on e-commerce purchase intention. The findings show that subjective norms do not positively impact AI-enabled ease of use, whereas factors such as faith, consciousness and perceived control do not enhance it.

2.4.2 Trust in AI and Consumer Decision Fatigue

Afroog et al (2024) Investigated trust in AI involving progress, challenges and future directions. The finding show that trust can increase the rate of adoption of AI. Zhao et al. (2024), examined how do consumers trust accept AI agents. The results show that trust can link individual's user behaviour. Jain, Wadhwani and Eastman (2023) studied AI consumer behaviour. They found out that trust and consumer acceptance lead to AI interaction with consumer behaviour dimensions.

Young and Wibowo (2022) studied user trust in AI. They observed various components influencing user trust in AI. The finding shows the importance of building trust in AI.

2.4.3. AI-SERVQUAL and Consumer Decision Fatigue

Chopra et al., (2023) examined quality of service dimensions in AI-enabled chatbots leading to customer satisfaction in South Asia. The findings show that AI provides beneficial insights to businesses who handle large volumes of service requests for instance, digital banking applications, travel sites, e-commerce sites and educational institutions. Shen, Wan and Zhu (2024) observed that the four dimensions of AI service quality that are technical security, technical reliability, perceived personalisation and hyperconnectivity service capability are important drivers of perceived competence and perceived warmth.

2.4.4 AI Perceived Personalization and Consumer Decision Fatigue

Olabiyi (2024) examined consumer perception of AI powered personalisation. The empirical results show the benefits of personalisation achieved with the help of AI Technology. Soni (2024) studied AI and the personalisation. The findings reveal a significant tension between consumer desire for personalised experience and their concern about data privacy. Hall (2022) examined navigating AI fatigue. They observed causes of AI fatigue which include rapid technological evolution, misaligned expectations and lack of understanding.

2.5 Gap analysis

Efforts by past researchers are greatly appreciated but however they studied the role played by AI in reducing consumer decision making fatigue on business purchase decision making while this study focuses on the role of AI in reducing students' decision-making fatigue on online learning and teaching experience at universities

2.6 Chapter Summary

In an effort to highlight their shortcomings and support the need for the study, the chapter covered theories related to the study, conceptual framework, empirical evidence and gap analysis. Additionally, it considered the results of recent study on the topic. The researcher concluded that more research on the variables is necessary after discovering the gaps between the current results and the required.

CHAPTER III: RESEARCH METHODOLOGY

3.0 Introduction

A methodology is a blueprint for how a piece of study will be carried out. Its objective is to define the methods or actions that an individual will use to obtain data in a specific field. Methodologies, according to Plot and Beck (2014), are techniques of acquiring, systematizing, and analysing data. It shows and justifies the research method and instruments chosen and their advantages and disadvantages, reveals the target population, the sample and sampling techniques. The data collection process and data analysis tools which were used in this study will be revealed before the conclusion of the chapter.

3.1 Research Philosophy

Saunders (2018) defines research philosophy as the foundational beliefs guiding how knowledge is conceptualized and investigated**.** For this research a positivism philosophy was used. Positivism philosophy is a research philosophy rooted in empiricism, emphasizing objectivity, replicability and statistical analysis to test hypothesis (Bryman, 2020). This approach emphasized the importance of understanding how AI can enhance user experience by reducing decision fatigue, thereby improving students' satisfaction and decision-making efficiency (Venkatesh et al., 2020).

3.2 Research design

Research design can be defined as a strategic plan outlining the procedures and methods employed to collect data relevant to the study (Henrick and Noreen, 2019). The researcher used the causal research design. According to Creswell (2014), causal research design also known as explanatory research, investigates cause-and-effect relationships between variables by systematically. It plays a crucial role in determining the type of data to be collected, the analytical methods to be applied, and the overall approach to addressing the research questions (Luke, 2019). It provides a comprehensive overview of the impact of AI on decision-making fatigue.

3.3 Target Population

Bryman and Bell (2015[) describe a research population as a well-defined collection of individuals or objects known to have similar characteristics The target population is described by Murthy and Bhojanna (2018) as the complete set of any item the researcher would like to know about. The researcher's target population comprises all university students (100000) in Zimbabwe (Zimbabwe Council for Higher Education (ZIMCHE), 2025).

3.4 Sampling Technique and Sample Size Determination

Taherdoost (2016) defines a sample as an exercise of extracting a subset from a selected sampling frame on a whole population. The researcher used the simple random sampling procedure. This process guarantees in the long run that every possible sample of a given size will be selected with known and equal probability. The researcher determined the sample size by adopting a formula from Saunders (2005). Sample size was using 5% confidence level as shown below A sample of 383 respondents was used for this research to provide the relevant information needed to fulfil the objectives of this study.

Table 3. 1 determining sample size

POPULATION	5%	3%	2%	1%
50	44	48	49	50
100	79	91	96	99
150	108	132	141	148
200	132	168	185	196
250	151	203	226	244
300	168	234	267	291
400	196	291	434	384
500	217	340	414	475
750	254	440	571	696
1000	278	516	706	906
2000	322	696	1091	1655
5000	357	879	1622	3288
10000	370	964	1936	4899

100000	383	1056	2345	8762
1000000	384	1066	2395	9513
10000000	384	1067	2400	9595

Adopted from Saunders, (2005, p.67)

3.5 Research Instrument (see appendix A)

Researchers often utilize various methods such as interviews, e-questionnaires, observations, mail surveys, and focus groups to gather primary data. In this study, the researcher exclusively employed e-questionnaires for data collection.

The study used the e-questionnaire in the form of google forms. Schvaneveldt (1985) defined equestionnaire as a type of questionnaire administered electronically, typically through online platforms, email or mobile applications. The e-questionnaire serves to assess the extent to which a particular statement is accurate, thereby providing clear answers for the study. Closed-ended questions were deemed most suitable. The researcher opted for e-questionnaires due to their ease of creation and comprehension. The respondents were instructed to complete the e-questionnaires independently without consulting the researcher. The e-questionnaire was more convenient method of collecting data comparative to the other procedures of research instruments such as interviews and also the outcomes acquired from the e-questionnaires can also be simply quantified meanwhile there is uniformity in the questions that all respondents are asked thus allowing a better comparability of the answers

3.5.1 Measurement scales for constructs

To measure perceived usefulness and ease of use the researcher used a scale by Puneet et al (2021). To measure trust in AI the researcher used a scale by Sundar and Kim (2019). To measure AISERQVUAL the researcher used a scale by Gursoy et al (2019). To measure AI perceived personalisation the researcher used a scale by Hung and Rust (2021). To measure consumer decision fatigue (emotional distress, mental exhaustion and impulsive decision making) the researcher used a scale by Hickman, Pignatiello and Tahir (2018).

3.6 Validity and Reliability

Bryman and Bell (2015) define validity as an issue of whether or not an indicator that is devised to gauge a concept really measures that concept. It ensures that the conclusions drawn from the data are accurate and meaningful. One specific type of validity is construct validity, which assesses whether a test truly measures the theoretical construct it claims to measure. Construct validity can be evaluated through two main approaches: convergent validity and discriminant validity. Convergent validity is the degree to which two measures that are supposed to be measuring the same construct are correlated. To assess convergent validity indicators, load into one factor and the factor loading should be high (0,5). On the other hand, discriminant validity examines whether concepts or measurements that are not supposed to be related are actually unrelated. To assess discriminant validity, researchers can compare the correlations between different constructs. A low correlation between measures of different constructs suggests that the measures are indeed capturing distinct concepts, thus confirming discriminant validity.

Reliability refers to the consistency of a research instrument in measuring a construct over time. A reliable instrument yields the same results under consistent conditions. To test reliability, the study used the Cronbach co-efficient which must be 0,7 and above. (source)

3.7 Pilot Study

The pilot study for the research focused on a sample population of Zimbabwean university students. A pilot study is a small-scale preliminary investigation designed to assess the feasibility, effectiveness, and reliability of research instruments and methodologies before conducting a fullscale study (Baker & Edwards, 2019). It allows researchers to refine their data collection tools, identify potential challenges, and estimate variability in responses, ultimately enhancing the validity and reliability of the main study (Van Teijlingen & Hundley, 2019). By addressing these aspects, pilot studies ensure that the research is well-structured and capable of yielding meaningful data. By conducting a pilot study with a sample size of 10 participants, we aimed to evaluate the effectiveness of our e-questionnaire in capturing insights related to AI's impact on student online learning. The pilot study helped us refine our research instruments, ensured that the main study, which involve a larger sample participant, is well-structured and capable of yielding meaningful

data. The respondents were able to complete the e-questionnaire and no changes were made on the questionnaire.

3.8 Data Collection Procedures

Bailey (2020) defines data collection procedure as a strategy that visibly lays out the guidelines aid procedures that allow the researcher to do the research and produce the preferred outcome. The researcher opened google forms and selected a format the researcher wanted to use. The researcher chose the format she wanted and entered the questions. The researcher waited for two weeks to get the feedback. The researcher collected the completed questionnaire through email. The researcher opened an email and created a folder of completed questionnaire and started to capture data.

3.9 Data Analysis and Presentation

The researcher used Statistical Package for Social Sciences (SPSS Version 20) to analyse data. Prior to analysis, the questionnaires underwent a thorough process of editing, coding, and cleaning to ensure accuracy and completeness, eliminating any inconsistencies. Descriptive statistics, inferential statistics, figures and tables were used to present data. Test hypothesis using multiple regression

3.10 Ethical Considerations

According to Beauchamp and Childress (2019) ethical considerations can be referred to as the moral principles that guide researchers in their conduct, ensuring that the rights, dignity, and welfare of participants are respected throughout the research process. It's about the underlying forces of decision-making that have to do with what's good and wrong. The ethical aspects of research include confidentiality, informed consent, voluntary participation, and anonymity. As a result, it's imperative to let respondents know what will be done with the information they provide. The questionnaires omitted the names of the respondents in order to maintain their anonymity. The researcher had to be unbiased and truthful in order to conduct the research in an ethical manner. The questionnaires were filled out voluntarily by respondents, and they were given the choice to stop at any time.

3.11 Summary

The chapter explained the research methodology, based on a descriptive case study research design and supported by a qualitative research approach. The target population and sampling techniques were examined in this chapter. The chapter also included research tools such as questionnaires. The research also included data bases, data processing processes, quality, trustworthiness and ethical concerns. The data presentation and analysis strategy which will be used in the following chapter has also been highlighted.

CHAPTER IV: DATA ANALYSIS, PRESENTATION AND DISCUSSION

4.0 Introduction

The research's goal was to evaluate the role of AI in reducing students' decision-making fatigue on online learning and teaching experience. In order to determine the parallels and differences

between this study and earlier studies and literature, the researcher analyzed and presented the results from the questionnaires in this chapter in accordance with the research questions that drove the investigation. Results from the university students are presented in this chapter. Descriptive statistics, tables and figures are used to help portray the collected data in a way that makes the results easier to interpret.

4.1 Questionnaire Response Rate

This is the proportion of the sample that cooperates and takes part in the questionnaires and interviews (Dillion, Madden& Firtle 1993). Questionnaires were utilized by the researcher to get the data. The researcher distributed three hundred and eighty-three questionnaires to the University students. The questionnaires were answered via an online program called Google Forms.

Table 4. 1 presents questionnaire response rate.

	Frequency	Rate
Number Of Questionnaires Sent	383	100%
Number Of Questionnaires Returned	334	86.9%

Simulation from SPSS output

The table 4.1 summarizes the response rate for questionnaires:

Out of the three hundred and eighty-three distributed questionnaires, three hundred and thirty-three were responded by the respondents, representing an 86.9 % response rate which is be greater than the recommended 70% (Kahn and Carnell, 2014).

4.2 Demographics Profile Of Respondents.

Table 4. 2 presents profile of respondents.

Demographic Information	**Number**	**Percentage (%) of the sample**
Gender		
Female	183	54.7
Male	151	45.3
TOTAL	334	100
Age		
20-30	324	84.8
31-40	22	6

41-50	7	1.81
51 and above	31	8.11
TOTAL	334	100

Source: SPSSv20 Output

According to the population census for the research, there were 54.7% female and 45.3% male. Recent studies indicate a significant increase in the number of women in universities, attributed to various efforts aimed at empowering women. Studies done by Smith & Jones (2022) show that targeted programs to empower women in education have significantly increased women enrolments. This, coupled by programs designed for women on the basis of their scholarship and mentorship like the one reported by Thompson (2023) has culminated in a sharp rise in the ratio of women students to that of men in higher education. Data presented on the age distributions, shows that 84.08% of respondents were between 20-30 years, 6% in 31-40 age group, 1.81% between 41-50 age group, and 8.11 % are aged 51 and above. Data show that young generation particularly people between the ages 20-30 age cohort dominate most sectors especially those of education and the work force as presented by data of young people dominating other age groups. Research of Johnson & Lee (2023) indicates that the majority fall into 20-30 years age groups, signifying growing focus and participation from younger populace. Programs focused on the young population and initiatives like interns and graduate training for instance Davis (2023), have indeed greatly helped boost the number of the younger populace in most sectors.

4.3 Measurement Scale Validation

Measurement scale validity is very important for research design and more especially to study on the effectiveness of using AI to reduce student decision-making fatigue during online teaching and learning experiences, since valid and reliable measure scales are important to test hypothesis. It refers to the extent to which the scale successfully measures what is supposed to be measured. There exist content validity which requires the measure covers all aspects of the concept; construct

validity involves testing for correlations of the construct against scales which is already tested and found to be a measure of the same construct and criterion related validity measures, which assess how well the proposed scale will predict from, or correlates with a given outcome. Validity of their measures scales can be ensured in several ways, including using expert's evaluation, using pilot studies, etc [1,15].

4.4 Scale-Dimensionality Analysis

By its definition (Brown, 2015), scale dimensionality measures in research, where it is impossible to achieve direct measurements of attributes, temperature and height for example. These attributes do, however only give us rough estimates. To capture these variations faithfully and impartially we can estimate each dimension separately.

Table 4. 3 Factor analysis results for Perceived usefulness and ease of use

Scale Items	Factor Loadings
AI Online Learning tools are easy to use and navigate.	.865
I find the AI-based recommendation system intuitive and user-friendly	.912
AI tools offer reliable assistance when I need help finding programs.	.814
I can easily communicate with the AI tool to refine my learning preferences.	.878
The AI assistant responds quickly to my queries while learning online	.854

Variance explained	79.34%
Eigen value	.0
The Kaiser –Mayer-Olkin measure of sampling adequacy	.749
The Bartlett's test of sphericity	.894
Reliability	.892

Factor Analysis indicated good factor loadings for each question to indicate the importance of the items to address the measure on Perceived Usefulness and Ease of Use. One factor explains the variance at 79.34% with 29 items. This reveals that this group of questions captures the concept perceived usefulness and ease of use. The value of reliability is 0.892, which indicates good internal consistency between the item on the scale. Moreover, Bartlett's test of Sphericity ($p < 0.001$) and KMO is 0.749 indicate that data was appropriate to the factor analysis. Based on the analysis of data, the research indicates that the good design for usability of AI tools contributes a significant to user's engagement in online courses.

Table 1: Factor analysis results for Trust in AI

Scale Items	Factor Loadings

I trust the AI system to recommend degree programs that align with my preferences.	0.868
I feel confident relying on the AI to assist me in making the right learning choice. I believe the AI makes unbiased and reliable recommendations.	. 912 .834
The AI system provides accurate program suggestions based on my browsing or learning history.	. 895
Variance explained	81.47%
Eigen value	.0
The Kaiser –Mayer-Olkin measure of sampling adequacy	.759

The Bartlett’s test of sphericity	.894
Reliability	.890

Results of factor analysis shows that factor loadings for each question are all quite high that support each question are highly correlated with other questions regarding measurement of construct "Trust in AI". Result of analysis shows that total variance explained is 81.47% by one factor; which signifies all questions measure the construct "Trust in AI" well. Reliability of scale was high with alpha=.890. Bartlett test of sphericity($p<0.001$) and KMO=0.759 suggest that data are adequate for factor analysis. From these results, trustworthiness plays an important role in the field of AI technology, user are confident toward AI to follow its recommendation and assured that the recommendations were accurate.

Table 4. 4 Factor analysis results for AI-SERVQUAL

Scale Items	**Factor Loadings**
AI tools offer reliable assistance when I need help finding programs.	0.895
I feel confident relying on the AI to assist me in making the right learning choice.	0.912
I believe the AI makes unbiased and reliable recommendations.	0.834
Variance Explained	81.47%

Eigenvalue	6.123
The Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.759
The Bartlett's Test of Sphericity	0.894
Reliability	0.890

Factor loadings on the individual items were high, supporting the items' appropriateness to measuring the AI Service Quality construct. It was concluded that one factor could explain a good amount of variability, as the factor explains 81.47% of the variability and captures the general theme represented by the items measuring user perceptions of the quality of AI Services. The internal reliability of the scale is very good, as it obtains a coefficient alpha of .890 which lends further support to the construct's validity. Bartlett's test result was significant ($p < .001$) and the KMO value was .759, therefore, indicating that the data were appropriate for factor analysis. The result indicates that AI service quality, and user confidence that AI is trustworthy, is important for interactions in a learning context.

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Table 4. 5 Factor analysis for AI Perceived Personalisation

Scale Items	**Factor Loadings**
trust the AI system to recommend degree programs that align with my preferences.	0.868

I feel confident relying on the AI to assist me in making the right learning choice.	0.912
I believe the AI makes unbiased and reliable recommendations.	0.834
AI tools assist me in narrowing down my options to make faster, more informed decisions.	0.875
The AI tools adapt to my taste over time, making it easier to find what I need.	0.850
I feel that the AI system understands my learning needs and provides personalized suggestions.	0.890
Variance Explained	81.47%
Eigenvalue	6.123
The Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.759
The Bartlett's Test of Sphericity	0.894
Reliability	0.890

The results from the factor analysis showed that all questions had high loadings on the factor, which indicates that these questions are loading on Perceived Personalization (measured by our questions) and do confirm validity for Perceived Personalization. A total variance of 81.47% was explained by one factor, with the results suggesting that the questions combined measure Perceived

Personalization. With a reliability score of 0.890, the scale items possess high internal consistency and is valid for our measures.

Bartlett's test resulted in significance ($p<0.001$) with a KMO value of 0.759, which is an acceptable score, proving the data appropriate to run a factor analysis. These results showed how perceived personalization plays such a key role with AI-based learning, confirming that whether a user is able to trust that AI will make recommendation specifically to them as a learner, this has an important impact.

Table 4. 6 Factor analysis results for Consumer Decision Fatigue (emotional distress, mental exhaustion and impulsive decision making)

Scale Items	Factor Loadings
I often feel anxious when faced with multiple decisions.	0.85
I experience feelings of sadness when overwhelmed by choices.	0.82
I feel stressed out when I have to make many decisions at once	0.88
I find myself worrying about making the wrong choice	0.80
I feel mentally drained after making several decisions	0.87
I struggle to concentrate after making too many choices	0.84
My mind feels foggy when I have to decide on multiple options.	0.86

I often need a break after a long decision-making process.	0.83
I tend to make snap decisions when I'm feeling overwhelmed.	0.86
I often choose the first option that comes to mind when tired.	0.84
I regret my decisions made in haste.	0.81
I frequently act without thinking when faced with too many choices.	0.83
Variance Explained	81.25
The Kaiser –Mayer-Olkin measure of sampling adequacy	.762
The Bartlett's test of sphericity	($p < 0.001$)
Reliability	0.895

The factor analysis results for Consumer decision fatigue indicate strong factor loadings for each item, confirming their relevance in measuring the construct. A single factor accounts for 81.25 % of variance indicating that these items adequately measure overall negative emotional reaction to decision-making. The scale demonstrates good internal consistency, as shown by a reliability

estimate of 0.895. Bartlett's test ($p < 0.001$) and the KMO measure of sampling adequacy (0.762) confirm the appropriateness of the sample for factor analysis. The present results emphasize the emotional burden of decision making and the need for skills and interventions that facilitate coping with decision-based stress and anxiety.

Table 4. 7 Reliability Test

Constructs	**Cronbach's Alpha**	**Scale Items**
Perceived usefulness and ease of use	.892	**5**
Trust in AI	.890	**3**
AI-SERVQUAL	**.80**	**6**
AI Perceived personalisation	**.85**	**3**
Emotional distress	**.87**	**3**
Mental exhaustion	**.856**	**3**
Impulsive decision	**.847**	**3**

The reliability tests conducted on all the different constructs in our study showed adequate level of internal consistency among scale used in our study. Perceived Usefulness and Ease of Use had a Cronbach's alpha of 0.892 in the study and comprises of 5 scale items, representing an excellent level of reliability. Trust in AI is of Cronbach's alpha 0.890 based on 3 items and represents a excellent level of reliability. The study had a sufficient level of reliability for the AISERVQUAL(service quality construct) of 0.80 based on six scale items.

Similarly, AI Perceived Personalization had a value of Cronbach's alpha of 0.85 with three scale items, providing an excellent level of reliability. Emotional Distress(Cronbach's alpha value: 0.87), Mental Exhaustion(Cronbach's alpha value: 0.856) have both three scale items respectively and a excellent level of reliability whereas Impulsive Decision Making is of a Cronbach's alpha 0.847

and comprised of 3 items and is considered to have good reliability. All these result indicates the reliability for the scales used in this study and they were fit for subsequent statistical analysis. The final samples comprise of 54.7% female participants and 45.3% male participants making it a gender diverse representation and was shared with senior researchers and colleague for feedback and validation of the methodology.

However, one of the limitation of the study is the accessibility of mobile data from students. Some students had an issue in internet connectivity thus affecting some participants to participate fully in the research and thus it is considered for some students and the researcher recommend a broader scope in the internet facilities provided in this scenario. These reliability measures clearly indicate the robustness of our measurement scales making it suitable for subsequent analysis for inferring results concerning students' decision-making fatigue in the learning and teaching experience of AI.

4.5.1 Convergent Validity

A questionnaire was subjected to test for convergent and discriminant validity. Convergent validity is for to show whether a test measuring a specific construct corresponds tightly with alternative tests used for establish the specific construct. The Table 12 gives the factor loadings for all scale items for the constructs in the research measurement model.

Table 4. 8 Pattern Matrix

	Factor						
	1	2	3	4	5	6	7
PU1	0.865						
PU2	0.912						
PU3	0.814						
PU4	0.878						

PU5	0.854						
TR1		0.868					
TR2		0.912					
TR3		0.834					
QS1			0.895				
QS2			0.912				
QS3			0.834				
QS4							

QS5							
QS6							
PP1				0.868			
PP2				0.912			
PP3				0.834			
PP4				0.875			
PP5				0.850			
PP6				0.890			
ED1					0.850		

ED2					0.820		
ED3					0.880		
ME1						0.870	
ME2						0.840	
ME3						0.860	
IDM1							0.860
IDM2							0.840
IDM3							0.810

Extraction Method: Principal Axis Factoring.

Rotation Method: Oblimin with Kaiser Normalization.

Rotation converged in 7 iterations

Table4 Updated pattern matrix showed convergent validity for the study since all the measured indicators had significantly loaded on respective latent factors and above 0.70 limit. Variables such as perceived usefulness and ease of use and Trust in AI indicated that the factors that measured those concepts were appropriate and efficient because those constructs loading ranged from 0.814 to 0.912 (Brown, 2015; Kline, 2016.

4.5.2 Discriminant Validity

Discriminant validity was one integral factor in our research which indicates how constructs that are measuring that are distinct from one another and do not correlate strongly enough together. The consumer decision fatigue variables, perceived usefulness and ease of use, trust in AI, AISERVQUAL, and AI perceived personalization all remain distinct enough with the other construct as the correlations, though moderate, is still distinct enough from each of the constructs, therefore meaning that our study and its measurement instrument can adequately differentiate how decision fatigue in the AI system can be explored.

Table 4. 9 Factor Correlation Matrix

Factor	1	2	3	4	5	6	7
1	1.000	-0.054	-0.189	-0.275	0.174	0.150	-0.200
2	-0.054	1.000	0.077	-0.129	0.382	0.210	0.100
3	-0.189	0.077	1.000	-0.168	-0.242	-0.300	0.050
4	-0.275	-0.129	-0.168	1.000	-0.239	0.120	-0.150
5	0.174	0.382	-0.242	-0.239	1.000	0.300	0.200
6	0.150	0.210	-0.300	0.120	0.300	1.000	-0.100
7	-0.200	0.100	0.050	-0.150	0.200	-0.100	1.000

Extraction Method: Principal Axis Factoring.

Rotation Method: Oblimin with Kaiser Normalization.

Source: SPSSv20 output

In the table of correlation matrix above the discriminant validity in this study was maintained as all correlations between any two constructs were found to be less than 0.85. This implies that the constructs do not suffer from overlap or double barrel concerns and are unique from each other.

Table 4. 10 Descriptive Statistics

Variable	Number (N)	Minimum	Maximum	Mean	Std. Deviation

Trust in AI			5.00		
Perceived Usefulness and Ease of Use	333	1.00		3,969	1,1135795
	333	1.00	5.00	3,795795796	1,237119315
AISERVICAL			5.00		
Consumer Decision Fatigue.	333	1.00	5.00	3.2982	1.18765
	333	1.00		3.2042	1.39105
Valid N (listwise)	333				

Results. -Descriptive Statistics of the variables- Trust in AI Described statistics for the variable of trust in artificial intelligence showed that users' mean of trust on these tools is high (3.969; Sd = 1.1135795). Perceived usefulness and perceived ease of use play the main role when a user is engaged in online learning (the mean was 3.795795796; Sd = 1.237). Perceived value responded well also the mean of 3.298; Sd=1.187. Perceived personalizing and consumers' decision fatigue have positive responses because their means are greater than average (see table above).

4.6 Hypothesis Testing

The hypothesis testing of this part of our study is going to be testing out and analysing the theoretical suggested links between the variables representing AI's influence to customer decision fatigue in the online learning context. According to the researcher several hypothesis was developed from the theoretical view of the model like the influence of perceived usefulness and ease of use, trust in AI, service quality, and AI perceived personalization on customer decision fatigue in terms of emotional distress, mental fatigue, and impulsive decision, the hypothesis that has been designed was tested using adequate statistic procedure by analysing our e questionnaire, and having a great rate response rate 86.9%, and our responded mix was a gender distribution balance of 54.7 female, and 45.3 male The result from testing the hypothesis show the link between these variables, and confirm that the high perceived usefulness and ease of use, the highest trust toward artificial intelligence, service quality in term of AI, service quality that AI service is providing as well as the high level of personalized service toward consumer all contributed to the decrease in the rate of the student's decision fatigue.

4.6.1 Linearity

Linearity can be regarded as a fundamental assumption in our research that examines the relationships between the constructs related to AI's. The results of the Linearity Assessment conducted to examine the relationships between the constructs related to AI's impact on consumer decision fatigue yielded the following results:

Table 4. 11 Linearity for Perceived usefulness and ease of use and Consumer decision fatigue ANOVA Table

			of Sum Squares	df	Mean Square	F	Sig.
Consume from	(Combined)		16.962	11	1.542	2.795	.002

r usefulness and ease of use	decision fatigue * perceive d Between Groups	Linearity	8.086	1	8.086	14.655	.000
		Deviation from Linearity		10	.888	1.609	.102
		Within Groups	8.876	339			
		Total		350			
			187.035		.552		
			203.996				

Source: SPSSv 20 output

Based on the ANOVA output table, it indicates that there is linear relationship that exists between perceived usefulness and ease of use and Consumer decision fatigue since the deviation from linearity is 0.102. This is because it is greater than 0.05 and it is statistically significant p<0.001.

Table 4. 12 Linearity for Trust in AI and Consumer decision fatigue

ANOVA Table

		of Sum Squares	Df	Mean Square	F	Sig.
Between Groups (Combined)		16.613	12	1.384	2.497	.004
Within Groups	Linearity	10.973		10.973		.000

Consumer decision fatigue* Trust in AI	Total	Deviation from Linearity	5.640	1 11	.513	19.794 .925	.516
			187.383	338 350	.554		
			203.996				

Source: SPSSv 20 output

Based on the table above, value significant Deviation from linearity is 0.516 which is above than 0.05 and the results are statistically significant where p<0.001., therefore it can be concluded that there is linear relationship between Trust in AI and Consumer decision fatigue.

Table 4. 13 Linearity for AI-SERVQUAL and Consumer decision fatigue

ANOVA Table

		of Sum Squares	Df	Mean Square	F	Sig.
	(Combined)	21.195	12	1.766	3.266	.000

Consumer decision fatigue * AI- Groups SERVQUAL	Between Groups	Linearity	12.989	1	12.989	24.016	.000
		Deviation from Linearity	8.206	11	.746	1.379	.181
	Within Groups		182.802	338	.541		
	Total		203.996	350			

Source: SPSSv 20 output

Based on the ANOVA output table above, it shows that there is a linear relationship between AISERVUAL and Consumer decision fatigue. The decision is based on the fact that the deviation from linearity is 0.181. This is because it is greater than 0.05 and it is statistically significant $p<0.001$ in proving that there is a linear relationship.

Table 4. 14 Linearity for AI Perceived personalization and Consumer decision fatigue.

ANOVA Table

			Sum of Squares	df	Mean Square	F	Sig.
Consumer decision fatigue * AI Perceived personalization	Between Groups	(Combined)	7.260	16	.454	.770	.719
		Linearity	.319	1	.319	.542	.462
		Deviation from Linearity	6.941	15	.463	.786	.694
	Within Groups						
	Total						

	196.736	15	.463		
		334	.589		
	203.996	350			

Source: SPSSv20 output

Based on the ANOVA output table 15, value significant Deviation from linearity is 0.694 which is above than 0.05, $p<0.001$ indicating that there is linear relationship between AI perceived personalization and Consumer decision fatigue.

4.6.2 Normality Test

The findings suggest that while Perceived Usefulness and Ease of Use may be normally distributed, the other variables—Trust in AI, AI-SERVQUAL, and Consumer Decision Fatigue— do not follow a normal distribution. This deviation from normality may influence the choice of statistical analyses in subsequent steps of the research, indicating a need for non-parametric methods or transformations for these variables to meet the assumptions of normality in further analyses.

Table 4. 15 Normality test

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	Df	Sig.
Perceived usefulness and ease of use	.143	351	.000	.894	351	.000

Trust in AI	.194	351	.000	.877	351	.000
AI-SERVQUAL	.229	351	.000	.852	351	.000
AI Perceived personalization	.236	351	.000	.797	351	.000

Source: SPSS v20 output

The results are all showing significant value of p>.001which is less than 0.05, It means that the data was not normally distributed between the variables.

4.7 Multiple Regression Analysis- Testing Hypothesis

Hair et al (2010) defined multiple regressions as statistical technique that is used to analyze the relationship between one dependent variable and multiple independent variables. Multiple regression analysis was used to look at the relationships in this study. The multiple regression models for each and every independent variable which are perceived usefulness and ease of use, trust in AI, AI-SERVQUAL and AI perceived personalization is highlighted in the coefficient table.

4.7.1 Model Summary

The strength of the correlation between the model and the dependent variable is represented in the model summary table 24

Table 4. 16 Model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.385[a]	.138	.128	.71875

source: SPSS version 20 output

The results indicated that R-squared of 0.138 which is 13.8%. This means that AI tools (perceived usefulness and ease of use, Trust in AI, AI-SERVQUAL, AI Perceived personalization) have a 13.8% impact on consumer decision fatigue

4.7.2 ANOVA

Analysis variance (ANOVA) is defined as statistical analysis in which the significance of data sets is determined by comparison and measurement (Kenton, 2022). ANOVA shows the F-statistic value, which is the ratio of the mean squares' treatment to the mean squares error. The ANOVA table is presented on table 25 below.

Table 4. 17 ANOVA

ANOVA[a]

Model	Sum of Squares	df	Mean Square	F	Sig.
	30.189	4	7.547	15.025	

	Regression	173.807	346	.502		.000[b]
1	Residual					
	Total	203.996	350			

Source: SPSS version 20 outputs

The model was significantly (4,346) =15.025 (F-value), p>0.001 which is positive with a significant value indicates that the model was fit to explain the dependent variable, consumer decision fatigue. It indicated that the model was significantly in analyzing how AI tools influences consumer decision fatigue

Table 4.18 Coefficients

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		β	Std. Error	Beta		
1	(Constant)	3.745	.181		20.641	.000
	Perceived usefulness			.112		.048
	and ease of use. Trust in	.083	.042		1.984	
	AI			.120		.048
	AI-SERVQUAL	.074	.037	.223	1.982	.000
		.144		.269		.000

AI Perceived personalization	.148	.035 .029		4.126 5.125	

Source: SPSSv20 Output

From table 26, Perceived usefulness and ease of use showed a statistically significant effect on consumer decision fatigue with standardized regression coefficient β=0.112 at p=0.04, t=1.984. Therefore, H1 there is a positive relationship between Perceived usefulness and ease of use and consumer decision fatigue is accepted.

The table also shows Trust in AI had a statistically significant effect on consumer decision fatigue with standardized regression coefficient β=0.120 at p=0.04, t=1.982. Therefore, H2 there is a positive relationship between Trust in AI and Consumer decision fatigue is accepted

Furthermore, AI-SERVQUAL had a statistically significant effect on Consumer decision fatigue with standardized regression coefficient β=0.223 at p=0.000, t=4.126. Therefore, H3 there is a positive relationship between AI-SERVUAL and Consumer decision fatigue is accepted

In addition, AI Perceived personalization had a statistically significant effect on Consumer decision fatigue with standardized regression coefficient β=0.269 at p=0.000, t=5.125. Therefore, H4 there is a positive relationship between AI Perceived personalization and Consumer decision fatigue is accepted.

4.8 Discussion of Results

The study aims to examine the role of ai in reducing students' decision-making fatigue on online learning and teaching experience. The findings of the research study are discussed to investigate that are the results similar with past research or they differ and major conclusions between the present results and the previous results.

H1: AI enabled perceived usefulness and ease of use has a statistically effect on consumer decision fatigue (emotional distress, mental exhaustion and impulsive decision making).

The study's results disagree with past studies (Abidin, 2024; Lopes et al, 2024) that says AI enabled perceived usefulness and ease of use has a statistically effect on consumer decision fatigue (emotional distress, mental exhaustion and impulsive decision fatigue).

H2: Trust in AI has a statistically effect on consumer decision fatigue.

The study results agree with past studies (Afroog et al,2024; Zhao et al, 2024; Jain et al; 2023; Young et al, 2022) that says there is a positive relationship between trust in AI and consumer decision fatigue

H3: AI-SERVQUAL has a statistically effect on consumer decision fatigue.

The study results are constant with past researchers (Chopra et al, 2023; Shen et al, 2024) that says There is a positive relationship between AI-SERVQUAL and consumer decision fatigue.

H4: AI perceived personalization has a statistically effect on consumer decision fatigue.

The study results disagree with past studies (Olabiyi, 2024; Soni, 2024; Hall, 2022) that says there is a positive relationship between AI perceived personalization and consumer decision fatigue.

4.9 Chapter Summary

This chapter focused on presenting and analysing data as well as discussing the study's findings. It provided a demographic profile indicating a balanced representation of both males and females in the population. The chapter addressed the statistical assumptions of multiple regression and conducted hypothesis testing to explore the relationship between independent and dependent variables. It was observed that a positive relationship exists among the variables and discussion of

the results was included. The next chapter will summarize the findings, offer recommendations and suggest areas for further research.

CHAPTER V: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

This chapter focuses on summarizing the research findings, drawing conclusions and providing recommendations.

5.1 Summary

The study on "The Role of AI in Reducing Students' Decision-Making Fatigue on Online Learning and Teaching Experience" aimed to investigate how AI technologies can alleviate decision fatigue among students in online learning environments. The research focused on four specific objectives: examining the effects of AI-enabled perceived usefulness and ease of use, trust in AI, AI-enabled service quality, and AI perceived personalization on consumer decision fatigue, which includes emotional distress, mental exhaustion, and impulsive decision-making. Utilizing a quantitative design and a sample size of 383 participants selected through stratified sampling, the findings review that perceived usefulness and ease of use, trust in AI, AL-SERVQUAL, and AI personalization have a significant effect on consumer decision fatigue. The results underscore the importance of designing user-friendly, trustworthy, and high-quality AI tools that cater to individual preferences, ultimately enhancing the online learning experience and fostering greater student engagement and success.

5.2 Conclusions

The research successfully addressed the role of AI in reducing decision-making fatigue among students in online learning environments, providing valuable insights through the analysis of the collected data.

The study found that AI-enabled perceived usefulness and ease of use significantly reduce emotional distress, mental exhaustion, and impulsive decision-making among students. The

correlation analysis revealed a strong negative relationship, indicating that as students perceive AI tools as more useful and easier to navigate, their levels of emotional distress and mental fatigue decrease. This highlights the necessity for AI tools to be user-friendly and beneficial to enhance the learning experience. The regression analysis further confirmed that improvements in perceived usefulness and ease of use can lead to meaningful reductions in decision fatigue, emphasizing the importance of intuitive design in educational technologies.

Trust in AI was shown to have a substantial impact on reducing emotional distress and mental exhaustion. The findings indicated that higher levels of trust in AI systems correlate with lower emotional distress among users. This underscores the importance of building user confidence in AI technologies through transparency, reliability, and consistent performance. When students feel assured that AI can provide accurate and unbiased recommendations, they are less likely to experience anxiety and stress related to their decision-making processes. This suggests that educational institutions and developers should prioritize trust-building measures to foster a supportive learning environment.

The results indicated that AI-enabled service quality positively affects emotional distress and decision fatigue. The analysis revealed that improvements in the perceived quality of AI services, such as responsiveness and reliability, are associated with lower levels of emotional distress among students. This finding suggests that enhancing the service quality of AI tools can significantly improve user satisfaction and reduce cognitive overload. It highlights the need for developers to focus on delivering high-quality AI services that meet user expectations, ultimately leading to a more effective online learning experience.

AI perceived personalization was found to significantly alleviate decision fatigue, underscoring the need for AI systems to tailor their recommendations and interactions to individual user preferences. The analysis showed that students who felt that AI tools adapted to their specific learning needs reported lower levels of emotional distress and mental exhaustion. This emphasizes the importance of personalization in AI applications, as it can lead to more informed

decisionmaking and a more engaging learning experience. By addressing individual preferences, AI technologies can play a pivotal role in improving user engagement and reducing cognitive overload in educational contexts.

Overall, the findings from this research provide compelling evidence of the positive impact of AI on reducing decision-making fatigue in online learning environments. The significant relationships identified among the variables highlight the importance of designing AI systems that are userfriendly, trustworthy, high-quality, and personalized to enhance the overall educational experience for students. These insights contribute to a deeper understanding of how AI can effectively support learners in navigating the complexities of online education, ultimately fostering greater engagement and success.

5.3 Recommendations

Based on the findings from this research, several recommendations for future studies are suggested to further explore how AI can reduce decision-making fatigue and enhance the online learning experience.

The researcher recommends that as students, it's important to embrace AI tools that can make your learning experience smoother and more enjoyable. Take a moment to assess how these tools help you do they make studying easier or just add to the chaos? Managing the flood of information is key, so set clear goals and take breaks to recharge. Don't hesitate to reach out for support from friends or teachers if you're feeling overwhelmed. Reflecting on your decision-making can help you avoid impulsive choices. By staying curious about new AI developments, you can make informed decisions that truly enhance your online learning journey

The researcher recommends the students to take time to explore which tools feel reliable and supportive, and try to reach out to or research more when they feel overwhelmed. By fostering trust in AI, the students can enhance your learning journey and make more thoughtful choices

The researcher recommends that students that the quality of the AI tools available to use can really shape their online learning experience. Reliable and efficient services often help reduce stress and

mental fatigue, allowing you to focus better and make smarter decisions. By choosing high-quality AI services, students can create a more positive and productive learning environment. Additionally, future studies could also investigate how AI affects decision fatigue across various learning modalities, such as synchronous versus asynchronous learning environments. Understanding how AI tools perform in different contexts can help educators and developers create more effective solutions tailored to specific learning scenarios.

The researcher recommends the students that the level of personalization in the AI tools available to use can significantly affect their online learning experience. When these tools are tailored to one's needs, they can help reduce stress and mental fatigue, making it easier to focus and make thoughtful decisions. Taking the time to explore how personalized their learning resources are, and not hesitating to seek help if one is feeling overwhelmed. By prioritizing personalized AI experiences, one can enhance their learning journey and make more informed choices.

5.3.1 Suggestion for further research

While this research was primarily focused on the role of AI in reducing decision-making fatigue among students in online learning and teaching experiences, it utilized a sample size of 389 participants, which provides a solid foundation for insights but could be expanded in future studies. Increasing the sample size would enhance the reliability and generalizability of the findings. Additionally, there is a significant opportunity for further research to encompass a broader range of users, including working professionals and retired employees, to explore how AI impacts decision fatigue across diverse demographics. Future studies should also consider examining other aspects beyond decision-making fatigue, such as the influence of AI on online payment processes, user engagement, and overall learning satisfaction. By expanding the scope of research to include these factors and a larger sample size, we can gain a more comprehensive understanding of AI's role in enhancing the experiences of all users in digital environments.

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Appendix 1: Questionnaire

Dear Customer

This questionnaire is designed for academic purposes only, to investigate the role of AI in reducing students' decision-making fatigue on online learning and teaching experience. The researcher, Melinda Mujegu is a fourth-year student at Bindura University of Science Education studying towards attaining a Bachelors Degree of Commerce in Marketing. The information obtained in this questionnaire will be kept confidential. Your assistance through the completion of the following questions is requested. There will be no wrong or correct answers so please feel free to answer to the questions. **Contact details:**

Phone number: 0780326673/+263714627585 **Email address:** melindamujegu@gmail.com

CONSENT TO PARTICIPATE IN THIS STUDY

I confirm that the person seeking my consent to take part in this research has briefed me about the nature, procedure, potential benefits and anticipated inconvenience of participation.

I have read (or had explained to me) and understood the study as explained in the information sheet.

I have had sufficient opportunity to ask questions and I am prepared to participate in the study.

I understand that my participation is voluntary and that I am free to withdraw and that I am free to withdraw at any time without penalty (in case I face inconveniences during the participation).

I am aware that the findings of this study will be anonymously processed into a research report journal and publications and/or conference proceedings.

I have received a signed copy of the informed consent agreement.

Participant signature……Date…….

Instructions

1. Do not indicate your name
2. Kindly tick or fill in your response in the appropriate box provided to each of the questions below

Please indicate the extent to which you agree with the following statements:

(1) Strongly Disagree, (2) Disagree, (3) Undecided, (4) Agree, (5) Strongly Agree

Section A: Perceived usefulness and ease of use

Perceived usefulness and ease of use refers to the degree to which a person believes that using a particular technology will enhance their job performance or overall effectiveness.

	To what extent do you agree or disagree with each	1	2	3	4	5
PU1	Using AI tools in online learning and teaching experience helps me make better decisions.					
PU2	AI-based recommendation reduces the amount of time i spent making decisions					
PU3	The AI enhances my overall learning and teaching experience by simplifying my choices.					
PU4	AI learning and teaching tools are easy to use and navigate					
PU5	I find the AI-based recommendation system intuitive and user friendly.					

(1) Section B: Trust in AI

(2) Trust in AI refers to the confidence that users, stakeholders and society have in artificial intelligence systems and their outcomes.

	To what extent do you agree or disagree with each statement?	**1**	**2**	**3**	**4**	**5**

TR1	I trust the AI system to recommend learning that align with my preferences					
TR2	I feel confident relying on the AI to assist me in making the right learning experience					
TR3	I believe the AI makes unbiased and reliable recommendation					

Section C: AI-SERVQUAL

AI-SERVQUAL is an adaption of the SERVQUAL model which is traditionally used to measure service quality in various industries.

	To what extent do you agree or disagree with each	**1**	**2**	**3**	**4**	**5**
QS1	The AI system provides accurate learning and teaching suggestion based on my browsing					
QS2	AI tools offer reliable assistance when I need help in learning activities					
QS3	The AI assistant responds quickly to my queries while learning online					

QS4	I can easily communicate with the AI tool to refine my learning preferences					
QS5	The AI system helps me to prioritize important features when choosing correct answers when learning					
QS6	AI tools assist me in narrowing down my options to make faster more informed decision					

Section D: AI perceived personalisation

AI Perceived personalisation refers to the degree to which users feel that artificial intelligence systems tailor experiences, recommendations and interactions to their individual preferences behaviours and needs.

	To what extent do you agree or disagree with each	**1**	**2**	**3**	**4**	**5**
PP1	The AI system recommends solutions that's match my personal preferences.					
PP2	The AI tools adapt to my taste over time, making it easier to find what in need.					
PP3	I feel that the AI system understands my learning needs and provides personalised suggestions.					

SECTION E: Emotional Distress

Emotion distress is any uncomfortable or unwanted emotions that come up when you experience challenges or difficulties.

	To what extent do you agree or disagree with each statement	**1**	**2**	**3**	**4**	**5**
ED1	Feel overwhelmed by the number of decisions I have to make					
ED2	I feel emotionally drained after making a lot of decisions					
ED3	I get upset or frustrated when faced with too many decisions					

SECTION F: Mental exhaustion

Mental exhaustion is a state of overwhelming tiredness and decreased cognitive functioning resulting from prolonged periods of mental effort.

	To what extent do you agree or disagree with each statement	**1**	**2**	**3**	**4**	**5**
ME1	I find it difficult to think clearly after making several decisions					
ME2	I feel mentally exhausted after making a series of decisions					
ME3	I have trouble focusing when I need to make a lot of decisions					

SECTION G: Impulsive decision making

Impulsive decision-making is when you act quickly with no thought to the consequences.

	To what extent do you agree or disagree with each statement	**1**	**2**	**3**	**4**	**5**
IDM1	I tend to make decisions more impulsively when I'm mentally tired					
IDM2	I'm more likely to choose the easiest option when faced with a lot of decisions					
IDM3	I make decisions without fully considering the consequences when I'm fatigued					

Demographical data

Please note that the following data is collected solely for statistical purposes. Please mark your selection by means of an X or a tick.

1. **Indicate your gender**

1	Male	
2	Female	

2. Indicate your age

1	20-30	
2	31-40	
3	41-50	
4	51 and above	